PressAcademia
www.pressacademia.org/journals/rjbm
RJBM
ISSN 2148-6689
Research Journal of Business and Management YEAR 2022 VOLUME 9 ISSUE 2

THE VOLATILITY SPILLOVER BETWEEN NFT INVESTMENT INDEX AND GLOBAL TECHNOLOGY INDEX: DCC-GARCH APPLICATION

DOI: 10.17261/Pressacademia.2022.1563
RJBM- V.9-ISS.2-2022(3)-p.85-91

Hilmi Tunahan Akkus[1], Samet Gursoy [2], Mesut Dogan[3]
[1]Balıkesir University, Savastepe Vocational School, Department of Wholesale and Retail, Balıkesir, Turkey.
tunaakkus@balikesir.edu.tr , ORCID: 0000-0002-8407-1580
[2]Burdur Mehmet Akif Ersoy University, Bucak ZTYO, Department of Customs Management, Burdur, Turkey.
sametgursoy@mehmetakif.edu.tr , ORCID: 0000-0003-1020-7438
[3]Afyon Kocatepe University, Bayat Vocational School, Department of Business Administration, Afyon, Turkey.
mesutdogan07@gmail.com , ORCID: 0000-0001-6879-1361

Date Received: March 25, 2022 **Date Accepted:** June 8,2022

To cite this document
Akkus, H.T, Gursoy, S.,Dogan, M., (2022). The volatility spillover between NFT investment index and global technology index: DCC-GARCH application. Research Journal of Business and Management (RJBM), 9(2), 85-91.
Permanent link to this document: http://doi.org/10.17261/Pressacademia.2022.1563

ABSTRACT
Purpose- NFT is a digital token that represents a unique, one-of-a-kind asset on the blockchain. In this respect, NFTs can be used to represent ownership of any unique asset. In this study, the volatility spillover relationship between the NFT Investment Index and the Global Technology Index (XTEC) is investigated.
Methodology- More than one GARCH type model has been developed that reveals the relationship between assets in financial markets. The DCC GARCH model was preferred because it is a current model that reveals the variable correlation coefficient depending on time. The DCC-GARCH method was preferred for modeling the volatility spillover in the study. Daily data covering the period 19.04.2021-22.04.2022 are used.
Findings- - According to the findings of the study; A mutual volatility spillover has been detected between the NFT Investment Index and XTEC. Accordingly, the 1% shock in XTEC increases the NFT Investment Index volatility by 0.24%, while the 1% shock in the NFT Investment Index increases the XTEC volatility by approximately 1.86%. The findings show that NFT Investment Index volatility is more effective on XTEC volatility.
Conclusion- Those who invest in NFT or technology markets and those who are considering investing should also take into account the developments in the other market in question in terms of risk management. In addition, market regulators should take a proactive approach by considering the impact and importance of NFT markets.

Keywords: Blockchain, crypto assets, DCC-GARCH model, Non-Fungible Token **(**NFT).
JEL Codes: G11, G14, G15

1. INTRODUCTION

One of the other blockchain-based assets that has not fallen off the agenda recently with cryptocurrencies is a digital asset called a unique token (non-fungible token - NFT). People's interest in NFT markets has increased even more, especially with the digital artwork called Everydays: The First 5000 Days, created by digital artist Mike Winkelmann using the pseudonym Beeple, sold at Christie's auction house on 12.03.2021 for approximately 69.3 million dollars. The first tweet of Twitter's co-founder Jack Dorsey, "just setting up my twttr" dated 21.03.2006, was certified as NFT and sold for approximately 2.9 million dollars, which also attracted people's attention to NFT markets. The sale of Beeple's digital artwork mentioned above coincides with the sale of Jack Dorsey's first tweet.

Blockchain can be seen as "a technology that transforms partial trust, which can be provided by a trusted third party, a central authority, into absolute trust without being dependent on a single leader (server) with its distributed architecture" (Güven and Şahinöz, 2018: 184). Blockchain is a technology that "provides a secure, transparent digital transaction ledger that allows data to be recorded and transferred over the internet as time-stamped, in a distributed structure, encrypted and immutable"

(Gul Senkardes, 2021: 155). In this context, money transfers can be made reliably with Bitcoin and other cryptocurrencies based on Blockchain technology, without the need for a trusted third party or central authority. These decentralized value storage and value transfer opportunities offered by blockchain technology can be used in other fields besides cryptocurrencies, in information storage and information transfer transactions as well as value. Applications related to NFT are among the activities that can be evaluated in this context.

In this study, the relationships between NFT Investments Index and the Global Technology Index (XTEC) are investigated. Studies investigating the relationships between NFT markets and different markets are relatively new. Current studies focus on the relationship between NFT markets and especially crypto currency markets. Studies investigating the relationship between NFT prices and XTEC have not been found in the literature. In this respect, the study is an original study. The results obtained from the study provide important information to investors, researchers and policy makers.

The next stages of the study are as follows: In the second part, the concepts of tokens and NFT are explained in detail. The third chapter includes a literature review. In the fourth chapter, there are explanations of the data used in the study and the method applied. In the fifth section, the empirical findings of the study are included, and in the sixth section, the results of the study are explained.

2. TOKEN AND NFT CONCEPTS

Unlike money, a token is a value used only to represent a certain right or asset, or an object used instead of money, limited to a certain purpose. Accordingly, while money can be used as money everywhere, token is an object that can only be used for certain purposes in certain areas. Tokens can also be divided into fungible and non-fungible.[1] Fungible tokens, in other words non-unique tokens, are tokens that meet a certain standard and therefore can be exchanged for their counterparts. A non-fungible token, or NFT, is a digital token that represents a unique, distinct asset on the blockchain. NFTs, which can be used to represent ownership of one-of-a-kind items, allow for the symbolization of assets such as art, collectibles, and even real estate (www.ethereum.org/en/nft/). According to another definition, NFTs can be music, in-game items, artwork, collectibles, etc. are transferable rights to digital assets (Ante, 2021: 1). Dowling (2022a: 1) also briefly defined NFT as “a blockchain-recorded right to a digital asset”. In the literature or in daily life, the concept of crypto-collectibles or digital collectibles is used as well as the concept of "non-fungible". NFTs are not equal because they are unique, so they are not interchangeable. The concept of non-interchangeability here is important. Although NFTs represent a value like money, it is possible to use or exchange two currencies of the same value, while NFTs cannot be used or exchanged interchangeably. As a result of the non-interchangeability of NFTs, NFTs serve as proof of reality and ownership in the digital world (Binance Academy, 2020).

While explaining the concept of token in the paragraph above, it was stated that the token represents a right or an asset. From this point of view, the question of what NFTs can represent is of critical importance. In addition to digital items, rarely physical collections can be represented by NFTs. But what is common is that digital artworks, songs, Graphics Interchange Format (GIF), and videos have their own NFT (Binance Academy, 2021). NFTs can be identified with digital artworks. But digital art is just one of the ways to use NFTs. Like title deed to any item in the digital or physical realm, NFTs can be used to represent ownership of any unique asset (www.ethereum.org/en/nft/).

Finally, NFTs can be sold in marketplaces with different features such as OpenSea, Nifty Gateway, Foundation, Rarible, SuperRare, Axie Marketplace.

3. LITERATURE REVIEW

Although there is a very large literature on cryptocurrencies, there are more theoretical explanations in the literature regarding newly developing NFTs, but there are very limited empirical studies. Bao and Roubaud (2022) conducted a systematic review of research studies on NFT published in journals indexed in Web of Science and ScienceDirect until April 2022, and as a result of the research, they found only 13 published articles in the relevant journals, mainly focused on asset pricing.

Ito, Shibano and Mogi (2022) investigated price bubbles in NFT markets in their study. Dowling (2022a) analyzes the price behavior in NFT markets. The studies investigating the relationships between NFTs and other assets are listed below.

[1] NonFungible.com (2022) also mentions a third classification as “semi-fungibility” for the fungibility of tokens depending on usage.

Ante (2021) explores the relationships between NFT markets and cryptocurrency markets. According to the results of the study; Bitcoin (BTC) and Ether (ETH) prices affect the NFT markets. In other words, the newly developing NFT market is driven by the cryptocurrency market.

Alawadhi and Alshamali (2022) investigated the relationships and volatility spillovers between NFT, DeFi and cryptocurrency markets. According to the results of the research, there are important relationships between NFTs and DeFi assets. Moreover, the volatility spillovers among non-traditional financial markets is very limited. As a result of the study, also weak volatility spillovers between NFTs and cryptocurrencies, low correlation between DeFi assets and cryptocurrencies were detected. DeFi assets appear to be relatively unconnected with the cryptocurrency markets.

Dowling (2022b) investigated the volatility spillover effects and the existence of co-movement between the crypto currency markets consisting of BTC and ETH and the 3 NFT (Decentraland LAND, CryptoPunk, Axie Infinity characters). According to the results of the research; there is low volatility spillovers between cryptocurrency and NFT asset groups. In this case, it is argued that the markets in question are quite different from each other. However, it has been determined that there are low spillovers among the NFT markets. On the other hand, according to the result of wavelet coherence analysis, it is stated that there is a lot of co-movement between Ether and Decentraland LAND pricing.

Pinto-Gutiérrez et al. (2022) are investigating the determinants of NFT attention (measured by Google searches with the topic "non-fungible token" and "NFT"). For this purpose, Google search queries, major cryptocurrency prices, VIX, gold and S&P 500 returns are included in the analysis. According to the results of VAR analysis; BTC returns from the previous week draw significant attention to NFTs. In addition, according to the results of wavelet coherence analysis, it was determined that investors were more interested in NFTs after the increases in both BTC and ETH returns. These results suggest that increases in underlying crypto currencies could explain the attention for NFTs.

Yousaf and Yarovaya (2022) investigated the return and volatility transitions between NFTs, DeFi and selected assets. According to the results obtained from the study; weak static returns and volatility spillovers were found between the new digital markets of NFTs and DeFi assets and selected markets, which are explained as new digital assets are still relatively separate from traditional asset classes. On the other hand, it has been found that the dynamic return and volatility connection is higher during the initial phase of the COVID-19 pandemic and the 2021 cryptocurrency bubble. Finally, it is suggested that investors and portfolio managers add NFTs and Defi assets to their gold, oil and stock portfolios to gain diversification benefits.

Studies in the literature on the relationships between NFTs and other assets are summarized in Table 1 below.

Table 1: Literature Summary

Source	Samples	Data and Frequency	Method
Ante (2021)	NFT sales volume, NFT number of active wallets, BTC and ETH	01.01.2018-16.05.2021 (Daily)	Impulse-response functions Johansen cointegration test Short-term Granger causality test
Alawadhi and Alshamali (2022)	4 NFT, 1 DeFi asset, BTC and ETH	15.01.2021-06.12.2021 (Daily)	Diebold-Yilmaz (2012) volatility spillover approach Karim vd. quantile connectedness approach Han vd. (2016) bivariate cross-quantilogram approach
Dowling (2022b)	3 NFT, BTC and ETH	03.2019-03.2021 (Weekly)	Diebold-Yilmaz (2012) volatility spillover approach Wavelet coherence analysis
Pinto-Gutiérrez et al. (2022)	BTC, ETH, NFT, VIX, gold and S&P 500 returns; BTC, ETH, NFT, CryptoPunk, Decentraland attention	01.12.2017-30.07.2021 (Weekly)	ADF unit root test Vector autoregressive models Wavelet coherence analysis Granger causality test
Yousaf and Yarovaya (2022)	5 NFT, 5 DeFi assets, gold, BTC, WTI and S&P 500	03.05.2018-01.07.2021 (Daily)	TVP-VAR Model VAR-BEKK-GARCH Model

As seen in the literature review results so far, empirical studies on NFT are both very limited and very recent. Because NFT markets are a newly emerging market. Of the studies described above in the literature, only Pinto-Gutiérrez et al. (2022), Yousaf and Yarovaya (2022) explained the relationships between stock indices and NFTs in their studies, but technology indices have not been discussed in any of these studies yet.

4. DATASET AND METHODOLOGY

This study investigates the existence of a relationship between NFT and XTEC. Therefore the DCC-GARCH model was run using daily data for the periods 19.04.2021-22.04.2022. All daily data of the variables were obtained from www.investing.com. First of all, the logarithm of the data of the raw price series was taken and included in the analysis, and the results obtained from the analysis were shared in the findings section. In case of creating the data set of the research take considered data constraint of the variables such as limited period range.

The DCC-GARCH model was preferred due to indicates the relationship between the variables while determining the volatility interaction and transfer of the DCC-GARCH model.

Multivariate GARCH models are very important from the finance literature. GARCH models, which are used extensively to examine the volatile interactions of financial variables; It is possible to specify Vector Error Correction (VECH) model, Baba, Engle, Kraft and Kroner (BEKK) model, Dynamic Conditional Correlation (DCC) model and Constant Conditional Correlation (CCC). The definitions of mean equations are the same in VECH, BEKK, DCC and CCC models. However, conditions differ in the estimation process of conditional variance (Sattary, 2014: 28-29).

Bollerslev, Engle and Wooldridge (1988) introduced multivariate GARCH models with the development of univariate ARCH and GARCH models. They developed "VEC parameterization" for the multivariate GARCH model and expressed the multivariate GARCH model as the VEC-GARCH model. Engle and Kroner (1995) developed the BEKK-GARCH model using the BEKK parameterization and brought it to the literature due to some problems arising from the VEC parameterization. Bollerslev (1990) stated that in multivariate GARCH models, conditional correlations should be taken into account as well as conditional variance. For this reason, he developed the "CCC" parameterization.

Thus, multivariate GARCH models were introduced to the literature as CCC-GARCH. Instead of the conditional correlation parameter used in the CCC-GARCH models, Tse and Tsui (2002) and Engle (2002) used the " DCC" parameterization. Thus, they developed the DCC-GARCH model.

$$r_t = \alpha + \sum_{i=1}^{k} \beta r_{t-i} + y_t \tag{1}$$

Equation (1) expresses the average model following a vector autoregressive (VAR) process of order k.

$$\gamma_{A,t} = \sqrt{h_{A,t}\varepsilon_{A,t}} \tag{2}$$

$$\gamma_{A,t} = \sqrt{h_{B,t}\varepsilon_{B,t}} \tag{3}$$

$$\rho_t = COV(\beta_{A,t}\beta_{B,t}) = (1-\theta_1-\theta_2)\rho + \theta_1\rho_{t-1} + \theta_2\Psi_{t-1} \tag{4}$$

As seen in Equation (4); ρ_t represents the non-constant correlation coefficient that changes with time. In order for the ρ correlation matrix to be of positive significance, the condition $0 \leq \theta_1$, $\theta_2 < 1$ ve $\theta_1 + \theta_2 \leq 1$ must be done (Hepsağ and Akçalı, 2016: 58).

$$\begin{bmatrix} h_{A,t} \\ h_{B,t} \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} + \begin{bmatrix} \emptyset_{1,1} & \emptyset_{1,2} \\ \emptyset_{2,1} & \emptyset_{2,2} \end{bmatrix} \begin{bmatrix} y_{A,t-1}^2 \\ y_{B,t-1}^2 \end{bmatrix} + \begin{bmatrix} \delta_{1,1} & \delta_{1,2} \\ \delta_{2,1} & \delta_{2,2} \end{bmatrix} \begin{bmatrix} h_{A,t-1} \\ h_{B,t-1} \end{bmatrix} \tag{5}$$

In the DCC-GARCH model, $\emptyset_{11}$ ve δ_{11} are parameters that express the volatility persistence of a financial asset. $\emptyset_{22}$ ve δ_{22} parameters are used to measure the volatility of another financial variable. At the same time, these parameters should be meaningful and have values close to 1. Whether there is a volatility interaction between the variables is explained by the parameters $\emptyset_{12}$ ve δ_{12}

Finally, the DCC-GARCH model not only identifies the volatility interaction between variables, but also estimates the time-varying correlation coefficient. Thus, it also explains the relationship between the returns of financial assets.

5. FINDINGS

In the application part of the study, NFT and XTEC returns were examined. In this direction, descriptive statistics on the variables were reported at first, then the results obtained through the DCC-GARCH model were also reported.

Table 2: Descriptive Statistics of Variables

	NFT	XTEC
Mean	0.9824	0.7968
Median	0.6952	0.7440
Maximum	74.2457	38.8961
Minimum	-57.5697	-41.5978
Standard Deviation	21.2569	11.2587
Skewness	0.1957	0.4986
Kurtosis	3.5697	2.5697
Jarque-Bera	7.5697	4.5987
Prob.	0.0267	0.0469

According to the descriptive statistics of NFT and XTEC return series, it is observed that the standard deviation values are larger than the average values of the return series. Looking at the Jarque-Bera test statistics, the return series do not offer a normal distribution.

Tablo 3: DCC-GARCH Model Results for NFT and XTEC Returns

	Coefficients	Standart Errors	T-statistics	Prob.
$\boldsymbol{\gamma_1}$	-2130.1038	4186.0508	-1.2689	0.2635
$\boldsymbol{\gamma_2}$	-17059.8657	79.1307	-1.5782	0.1426
$\emptyset_{11}$	0.2407	0.3981	0.9651**	**0.0257**
$\emptyset_{12}$	0.8628	0.4828	4.9800**	**0.0169**
$\emptyset_{21}$	1.8624	0.8693	2.6694*	**0.0856**
$\emptyset_{22}$	0.6843	0.6971	1.10537	0.2489
$\boldsymbol{\delta_{11}}$	0.6700	0.4856	4.9939**	**0.0189**
$\boldsymbol{\delta_{12}}$	-0.5035	0.2939	-2.0567	0.1500
$\boldsymbol{\delta_{21}}$	-0.4060	0.8037	-0.9657	0.8425
$\boldsymbol{\delta_{22}}$	0.1222	0.6125	0.1900**	**0.0469**
$\boldsymbol{\theta_1}$	0.2837	0.0458	5.0597***	**0.0008**
$\boldsymbol{\theta_2}$	0.6614	0.0752	5.0368***	**0.0098**

Note: ***, ** and * denote statistically significance level at the 1%, 5% and 10%, respectively.

According to the findings of the DCC-GARCH model of NFT and XTEC returns presented in Table 3, it was determined that volatility occurred in NFT since the parameters $\emptyset_{11}$and δ_{11}, which explain the persistence of NFT volatility, are significant at the 5% significance level. According to the sum of these parameters, NFT volatility shows continuity with a value of 0.9093. Likewise, it was reached slightly less volatility persistence regard to explaining XTEC volatility $\emptyset_{22}$ and δ_{22} parameters with a total value of 0.8065.

On the other hand, only δ_{22} was found to be significant at the 5% significance level that explain volatility persistance of XTEC while $\emptyset_{22}$ is not significant by the value of the probability value of 0.2489.

1% of shock in NFT increases XTEC volatility by 1.8624%. Considering the volatility interaction between NFT and XTEC, NFT shocks affect XTEC just as NFT shocks affect XTEC. In this case, it is possible to say that there is a bidirectional volatility interaction between NFT and XTEC. The parameters θ_1 ve θ_2 which express the dynamic correlation relationship between NFT and XTEC, are statistically significant at the 1% significance level. Thus, there is a positive and strong relationship between returns that changes over time.

6. CONCLUSION

The digital transformation, which has accelerated in the Global Markets, has become an increasingly challenging structure in recent years. At the forefront of these transformations are the blockchain system, cryptocurrencies and other digital asset markets created in this direction. In a classical saying, people used to go away for miles to see each other, to meet, and therefore to be in the same environment. This situation was carried out for business negotiations and consultations. But today, it is unknown whether humanity is for the purpose of communicating faster or because it has become more selfish. Now, this need is met with digital channels. Even today's people prefer to see a work of art digitally, attend a concert, and spend time together in an environment where they can socialize. Here, the NFT system, which is also the subject of this study, is mentioned. In short, NFT is a technology that gives ownership to digital assets and registers their authenticity. Accordingly, the cost of using this technology and the investment and profitability of this technology are questioned. Because NFT investments are directly related to the technology sector, the relationship between technology sector profitability and NFT investments should be closely monitored.

This study focused on the volatility relationship between NFT investments and stock returns of global technology companies. DCC-GARCH model was applied to investigate the volatility relationship between NFT investment index and the Global Technology Index by using daily data in period of 19.04.2021-22.04.2022.

According to the findings of the DCC-GARCH model, the results are significant at 5% significance level. It is determined that volatility occurs in NFT, and this volatility persistence is higher when compared to the XTEC since the parameters $\emptyset_{11}$and δ_{11} which explain the persistence of NFT investments volatility. This means that is, a shock in the NFT lasts longer and is more susceptible to external interactions. In addition, the 1% unit shock in the XTEC increases NFT volatility by 0.24. 1% shock in NFT increases the XTEC volatility by 1.8624%. Based on the θ_1 ve θ_2 parameters, it was determined that the relationship between NFT investments and the XTEC is in a two-way positive correlation. Under the assumption of the model used in this study, the data range and the number of selected variables; It is concluded that NFT investments are affected by global technology indices in the same direction. It is an empirical finding for individuals and institutions that will invest in this field, and it is hoped that it will also contribute to the literature. According to these findings; those who invest in NFT or technology markets and those who are considering investing should also take into account the developments in the other market in question in terms of risk management. In addition, market regulators should take a proactive approach by considering the impact and importance of NFT markets.

In future studies, the existence of price bubbles can be investigated in the NFT market, where prices grow very rapidly. Likewise, the relationships between other blockchain-based assets such as DeFi assets, Metaverse, cryptocurrencies and technology indices can be investigated apart from the NFT market. Also, for similar studies to be carried out in this area, it is recommended to make an application that includes variables such as (political economic uncertainties, news spreading with the sector, energy costs, etc.) that are expected to have a direct and more direct effect on NFT investments.

REFERENCES

Alawadhi, K. M. & Alshamali, N. (2022). NFTs Emergence in Financial Markets and their Correlation with DeFis and Cryptocurrencies. Applied Economics and Finance, 9(1), 108-120.

Ante, L. (2021). The Non-Fungible Token (NFT) Market and Its Relationship with Bitcoin and Ethereum. Blockchain Research Lab, BRL Working Paper Series No. 20.

Bao, H., & Roubaud, D. (2022). Non-Fungible Token: A Systematic Review and Research Agenda. Journal of Risk and Financial Management, 15(5), 215. https://www.mdpi.com/1911-8074/15/5/215 (Date Accessed: 29.05.2022).

Binance Academy (2020). Kripto Koleksiyonlukları ve Benzersiz Tokenler (NFT) Rehberi. https://academy.binance.com/tr/articles/a-guide-to-crypto-collectibles-and-non fungible-tokens-nfts (Date Accessed: 24.05.2022).

Binance Academy (2021). Kendi NFT'lerinizi Nasıl Üretebilirsiniz? https://academy.binance.com/tr/articles/how-to-make-your-own-nfts (Date Accessed: 24.05.2022).

Bollerslev, T. (1990). Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized ARCH Model. The Review of Economics and Statistics, 72(3), 498-505.

Bollerslev, T., Engle, R. F. & Wooldridge, J. M. (1988). A Capital Asset Pricing Model with Time-Varying Covariances. Journal of Political Economy, 96(1), 116–131.

Diebold, F. X. & Yilmaz, K. (2012). Better to Give than to Receive_Predictive Directional Measurement of Volatility Spillover. International Journal of Forecasting, 28(1), 57-66.

Dowling, M. (2022a). Fertile LAND: Pricing Non-Fungible Tokens. Finance Research Letters, 44, 102096.

Dowling, M. (2022b). Is Non-Fungible Token Pricing Driven by Cryptocurrencies? Finance Research Letters, 44, 102097.

Engle, R. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. Journal of Business & Economic Statistics, 20(3), 339–350.

Engle, R. F. & Kroner, K. F. (1995). Multivariate Simultaneous Generalized ARCH. Econometric Theory, 11(1), 122-150.

Gul Senkardes, C. (2021). Blockchain Technology and NFT's: A Review in Music Industry. Journal of Management, Marketing and Logistics (JMML), 8(3), 154-163.

Güven, V. & Şahinöz, E. (2018). Blokzincir - Kripto Paralar - Bitcoin: Satoshi Dünyayı Değiştiriyor. İstanbul: Kronik Kitap.

Han, H., Linton, O., Oka, T., & Whang, Y. J. (2016). The Cross Quantilogram: Measuring Quantile Dependence and Testing Directional Predictability between Time Series. Journal of Econometrics, 193(1), 251-270.

Hepsağ, A. & Akçalı, B. Y. (2016). Türk Finans Piyasasında İşlem Gören Bankalar İle ABD Finans Piyasası Arasındaki Volatilite Etkileşiminin Analizi. Avrasya Ekonometri İstatistik ve Ampirik Ekonomi Dergisi, 1(1), 54-72.

Ito, K., Shibano, K. & Mogi, G. (2022). Predicting the Bubble of Non-Fungible Tokens (NFTs): An Empirical Investigation. https://arxiv.org/abs/2203.12587 (Date Accessed: 26.05.2022).

NonFungible.com (2022). NFT Market Quarterly Report: Q1 · 2022. https://nonfungible.com/reports/2022/en/q1-quarterly-nft-market-report-free/thank-you (Date Accessed: 29.05.2022).

Pinto-Gutiérrez, C., Gaitán, S., Jaramillo, D. & Velasquez, S. (2022). The NFT Hype: What Draws Attention to Non-Fungible Tokens? Mathematics, 10(3), 1-13.

Sattary, A. (2014). Petrol Fiyatları İle Hisse Senedi Getirileri Arasında Oynaklık Geçişkenliğinin Analizi Ve Portföy Yönetimine Yansımaları. Yayımlanmamış Doktora Tezi. Atatürk Üniversitesi Sosyal Bilimler Enstitüsü, Ekonometri Anabilim Dalı.

Tse, Y. & Tsui, A. (2002) A Multivariate GARCH Model with Time-Varying Correlations. Journal of Business and Economic Statistics, 20, 351-362.

www.ethereum.org/en/nft/ (Date Accessed: 25.05.2022).

www.investing.com (Date Accessed: 25.04.2022).

Yousaf, I. & Yarovaya, L. (2022) Static and Dynamic Connectedness between NFTs, Defi and Other Assets: Portfolio Implication. Global Finance Journal, 53, 100719.